TITLE OF THE INVENTION

A Method for Lighting- and View-angle-invariant Face Description with first- and second-order Eigenfeatures

BACKGROUND OF THE INVENTION

This invention relates to a method for lighting- and view-angle-invariant face description with first- and second-order eigenfeatures, and can be used in face description and recognition for content-based image retrieval, huma face identification and verification for bank, security system, and video phone, surveillance and tracking, digital library, and internet multimedia database.

Human face perception is an active area in the computer vision community. Face recognition will play an important role in multimedia database search and many other applications. In recent years considerable progress has been made on the problems of face detection and recognition. Different specific techniques were proposed. Among these, neural nets, elastic template matching, Karhunen-Loeve expansion, algebraic moments and isodensity lines are typical methods.

Among these methods, Principal component analysis (PCA) or Karhunen-Loeve expansion is an important branch. Eigenface method is derived from PCA and it is convenient to be computed and has consistent accuracy in identification. Prior work showed that the PCA approach dissociates spontaneously between different types of information. The eigenvectors with large eigenvalues capture information that is common to subsets of faces and eigenvectors with small eigenvalues capture information specific to individual face. The studies show that only the information contained by the eigenvectors with large eigenvalues can be generalized to new faces that are not trained.

The advantage of eigenface method is that eigenvectors with large eigenvalues convey information relative to the basic shape and structure of the faces. That means features extracted from eigenvectors with large eigenvalues can be used to describe major characteristics of human faces. However, this is also the weakness of PCA. If we only consider the features extracted from eigenvectors with large eigenvalues, we cannot get the details of the faces which corresponds to individual faces. If these details of individual face can be described with the common features of human faces, the description of human faces can be more accurate.

Furthermore, it is difficult to get suitable eigenvectors to represent human faces if the face images are taken under different lighting conditions and different view-angles. According to our experience, the regular eigenface method is not excellent in recognizing faces under different lighting condition. However, many face images of the same person are taken under different lighting and view-angle conditions. The lighting-invariant and view-angle-invariant face description is still an important field to be explored.

SUMMARY OF THE INVENTION

Eigenface method is effective to extract common face characteristics such as shape and structure. In order to get details of faces that are lost when eigenvectors with small eigenvalues are truncated, the reconstructed faces with the features from eigenvectors with large eigenvalues should be obtained. With the reconstructed face images, the residue images between original images and reconstructed images can be obtained. These residue faces can be looked as high-passed face images which still contain rich detailed information for individual faces. In order to describe these residue faces, eigenface method can be used on these residue faces again. The obtained eigenvectors with large eigenvalues will reveal the common characteristics of residue faces. With this method, the second-order eigenvectors with large eigenvalues can be obtained to extract corresponding features. According to our experiments, first-order and second-order eigenfeatures are both effective for the view-angle-invariant face description, while the second-order eigenfeatures are also effective for the lighting-invariant face description. Therefore, the combination of first-order and second-order eigenfeatures can be used for view-angle-invariant face description and the second-order eigenfeatures can be used for lighting-invariant face description. Another way to describe face is to use first-order eigenfeatures exclusively. For lighting-invariant face description, only the eigenfeatures extracted from the eigenfaces with the top k-th to N-th largest eigenvalues (where $0<k<N$) to avoid the lighting variance coming from the top k eigenfaces with largest eigenvalues. The view-angle-invariant face features can be the eigenfeatures extracted from the eigenfaces corresponding to the top N largest eigenvalues.

Besides, when we consider face description, an important characteristic is symmetry of faces. The faces of most of the people are symmetric. Thus we can consider to use the left-right mirrored face image to represent the same person. Consequently the eigenfeatures of the original image and the mirrored image can both represent the same person. Therefore, we can use the linear combination of the

eigenfeatures of the two images to represent the original image. In order to discriminate between the original image and the mirrored image, different weights can be used to combine the eigenfeatures.

The present invention provides two methods for lighting-invariant and view-angle-invariant human face description which can be used for image retrieval (query by face example), person identification and verification, surveillance and tracking, and other face recognition applications. In order to describe face characteristics, the concept of second-order eigenfaces is proposed according to our observation and derivation. At first, the first-order eigenfaces and second-order eigenfaces can be derived from a set of training face images. Then the eigenfaces can be adjusted with the characteristic of symmetry of faces. With these adjusted eigenfaces, the adjusted first-order and second-order eigenfeatures can be obtained. The combination of these eigenfeatures can be used to describe faces. With this description, Euclidean distance can be used for similarity measurement.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 is a diagram for generating the light-invariant face descriptor.

Figure 2 is a diagram for generating the view-angle-invariant face descriptor.

Figure 3 shows the procedure to mirror an eigenface.

Figure 4 shows the reconstructed faces, the corresponding original faces and the second –order residue images.

Figure 5 shows the procedure for computing the first –order feature $W^{(1)}$

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

According to the present invention, first-order Eigenface and second-order Eigenface are obtained.

In Figure 2, the face pictures 1a, 2a, 3a, 4a, 5a and 6a shown in the middle row are original face images captured by a digital camera without any particular processing. The face picture 1a can be expressed, by using one dimensional vector, as an original face image Φ_1. Similarly, face pictures 2a, 3a, 4a, 5a and 6a can be expressed respectively, as original face images Φ_2, Φ_3, Φ_4, Φ_5 and Φ_6. Generally, the original face image ia is expressed as Φ_i.

In the example shown in Figure 2, when one dimensional vectors of the six original face images are added and the sum is divided by six, an average image Ψ is

obtained, as given below.

$\Psi = (\Phi_1 + \Phi_2 + \Phi_3 + \Phi_4 + \Phi_5 + \Phi_6)/6$

A difference between the one dimensional vector Φ_1 of the face picture 1a and the average image Ψ is expressed as $\Gamma_1^{(1)}$. A similar differences $\Gamma_2^{(1)}$, $\Gamma_3^{(1)}$, $\Gamma_4^{(1)}$, $\Gamma_5^{(1)}$, $\Gamma_6^{(1)}$ can be obtained for other face pictures 2a, 3a, 4a, 5a and 6a, respectively. Thus, the following equations are obtained.

$$\Gamma_1^{(1)} = \Phi_1 - \Psi$$

$$\Gamma_2^{(1)} = \Phi_2 - \Psi$$

$$\Gamma_3^{(1)} = \Phi_3 - \Psi$$

$$\Gamma_4^{(1)} = \Phi_4 - \Psi$$

$$\Gamma_5^{(1)} = \Phi_5 - \Psi$$

$$\Gamma_6^{(1)} = \Phi_6 - \Psi$$

As will be described later, the difference $\Gamma_1^{(1)}$ will be used as a base for obtaining the first-order feature component $w_1^{(1)}$. Similarly, $\Gamma_2^{(1)}$, $\Gamma_3^{(1)}$, $\Gamma_4^{(1)}$, $\Gamma_5^{(1)}$, $\Gamma_6^{(1)}$ will be used as bases for obtaining the first-order feature components $w_2^{(1)}$, $w_3^{(1)}$, $w_4^{(1)}$, $w_5^{(1)}$ and $w_6^{(1)}$. In these formulas, the superscript (1) indicates that the formulas are related to the first-order feature.

When the differences $\Gamma_1^{(1)}$, $\Gamma_2^{(1)}$, $\Gamma_3^{(1)}$, $\Gamma_4^{(1)}$, $\Gamma_5^{(1)}$, $\Gamma_6^{(1)}$ are processed in a low pass filter, reconstructed matrixes $\hat{\Gamma}_1^{(1)}$, $\hat{\Gamma}_2^{(1)}$, $\hat{\Gamma}_3^{(1)}$, $\hat{\Gamma}_4^{(1)}$, $\hat{\Gamma}_5^{(1)}$ and $\hat{\Gamma}_6^{(1)}$ are obtained.

In Figure 2, the face pictures 1b, 2b, 3b, 4b, 5b and 6b shown in the top row

are reconstructed face images obtained by adding the average image Ψ to each of the reconstructed matrixes $\hat{\Gamma}_1^{(1)}$, $\hat{\Gamma}_2^{(1)}$, $\hat{\Gamma}_3^{(1)}$, $\hat{\Gamma}_4^{(1)}$, $\hat{\Gamma}_5^{(1)}$ and $\hat{\Gamma}_6^{(1)}$. The reconstructed face images 1b, 2b, 3b, 4b, 5b and 6b can be expressed as $\hat{\Phi}_1$, $\hat{\Phi}_2$, $\hat{\Phi}_3$, $\hat{\Phi}_4$, $\hat{\Phi}_5$ and $\hat{\Phi}_6$ respectively, as given below.

$$\hat{\Phi}_1 = \Psi + \hat{\Gamma}_1^{(1)}$$
$$\hat{\Phi}_2 = \Psi + \hat{\Gamma}_2^{(1)}$$
$$\hat{\Phi}_3 = \Psi + \hat{\Gamma}_3^{(1)}$$
$$\hat{\Phi}_4 = \Psi + \hat{\Gamma}_4^{(1)}$$
$$\hat{\Phi}_5 = \Psi + \hat{\Gamma}_5^{(1)}$$
$$\hat{\Phi}_6 = \Psi + \hat{\Gamma}_6^{(1)}$$

Since the reconstructed face images contains data that have been processed in the low pass filter so that the high frequency information is removed, the face information will not vary even if the angle of the face should be changed slightly.

In Figure 2, the face pictures 1c, 2c, 3c, 4c, 5c and 6c shown in the bottom row are residue images $\Gamma i^{(2)}$, which are obtained by subtracting the reconstructed face images from the original face images. Thus, the following equations can be obtained.

$$\Gamma_1^{(2)} = \Phi_1 - \hat{\Phi}_1 = \Gamma_1^{(1)} - \hat{\Gamma}_1^{(1)}$$
$$\Gamma_2^{(2)} = \Phi_2 - \hat{\Phi}_2 = \Gamma_2^{(1)} - \hat{\Gamma}_2^{(1)}$$
$$\Gamma_3^{(2)} = \Phi_3 - \hat{\Phi}_3 = \Gamma_3^{(1)} - \hat{\Gamma}_3^{(1)}$$
$$\Gamma_4^{(2)} = \Phi_4 - \hat{\Phi}_4 = \Gamma_4^{(1)} - \hat{\Gamma}_4^{(1)}$$
$$\Gamma_5^{(2)} = \Phi_5 - \hat{\Phi}_5 = \Gamma_5^{(1)} - \hat{\Gamma}_5^{(1)}$$
$$\Gamma_6^{(2)} = \Phi_6 - \hat{\Phi}_6 = \Gamma_6^{(1)} - \hat{\Gamma}_6^{(1)}$$

During the process of obtaining the residue images, the brightness information, caused by the lighting system, contained in the original face image and the same brightness information contained in the reconstructed face image are counterbalanced by the subtraction. Thus, the residue images will not be influenced by the lighting system.

The present invention will be further described using general formulas.

Consider an image Φ_i among a collection of M images (in the above

example, six images)(step 110 in Figure 1), where Φ_i is a one dimensional vector of raster-scanned image, define Ψ as the average image (step 120 in Figure 1):

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Phi_i \qquad (1)$$

Every image differs from the average image by a vector $\Gamma_i^{(1)} = \Phi_i - \Psi$ (step 130 in Figure 1). The covariance matrix of the data is thus defined as:

$$Q = A^{(1)}A^{(1)^T} \qquad (2)$$

where $A^{(1)} = \left[\Gamma_1^{(1)}\Gamma_2^{(1)}...\Gamma_M^{(1)}\right]$.

This is shown in step 140 in Figure 1.

Note that Q has dimension $wh \times wh$ where w is the width of the image and h is the height. The size of this matrix is enormous, but since we only sum up a finite number of image vectors M, the rank of this matrix can not exceed M-1. We note that if $v_i^{(1)}$ is the eigenvector of $A^{(1)^T}A^{(1)}$ (i=1,2,...,M) (step 150 in Figure 1), then $A^{(1)^T}A^{(1)}v_i^{(1)} = \lambda_i^{(1)}v_i^{(1)}$ where $\lambda_i^{(1)}$ are the eigenvalue of $A^{(1)^T}A^{(1)}$, then $A^{(1)^T}v_i^{(1)}$ are the eigenvectors of $A^{(1)}A^{(1)^T}$ as we see by multiplying on the left by $A^{(1)}$ in the previous equation:

$$A^{(1)}A^{(1)^T}A^{(1)}v_i^{(1)} = A^{(1)}\lambda_i^{(1)}v_i^{(1)} = \lambda_i^{(1)}A^{(1)}v_i^{(1)}$$

But $A^{(1)^T}A^{(1)}$ is only of size $M \times M$. So defining $u_i^{(1)}$ the eigenvector of $A^{(1)}A^{(1)^T}$ we have

$$u_i^{(1)} = A^{(1)}v_i^{(1)} = \sum_{k=1}^{M} v_{ik}^{(1)}\Gamma_k^{(1)}$$

The eigenvalue $\lambda_i^{(1)}$ is the variance along the new coordinate space

spanned by eigenvectors $u_i^{(1)}$ (step 160 in Figure 1). From here on we assume that the order of i is such that the eigenvalues $\lambda_i^{(1)}$ are decreasing. The eigenvalues are decreasing in exponential fashion. Therefore we can project a face image $\Gamma^{(1)}$ onto only $M_1 << M$ dimensions by computing $W^{(1)} = \{w_k^{(1)}\}$ where $w_k^{(1)} = u_k^{(1)^T}\Gamma^{(1)}$ and $1 \le k \le M_1$. $w_k^{(1)}$ is the k-th coordinate of $\Gamma^{(1)}$ in the new coordinate system. In this context, $W^{(1)}$ is called first –order features. The vectors $u_k^{(1)}$ are actually images, and are called first-order eigenfaces (in general, it is called eigenfaces in other documents). Let $U^{(1)} = [u_1^{(1)} u_2^{(1)} \ldots u_{M_1}^{(1)}]$ (step 170 in Figure 1), then

$$W^{(1)} = U^{(1)^T}\Gamma^{(1)} \qquad (3)$$

This is shown in step 180 in Figure 1.

Figure 3 shows the procedure for computing first-order features $W^{(1)}$. In the figure, eig(B,i) is the function to compute the i^th largest eigenvalue and its corresponding eigenvector of matrix . 320 is re-shaping, 340 is mirroring and 360 is re-shaping.

From Eq.(3), an interesting byproduct is that we can get a reconstructed matrix from $W^{(1)}$. Since $U^{(1)}$ is an $M_1 \times P$ matrix, we cannot get its inverse. However, we can use its pseudo inverse to approximate its inverse. Let $U^{(1)^+}$ be the pseudo-inverse of $U^{(1)^T}$, then

$$\hat{\Gamma}^{(1)} = U^{(1)^+}W^{(1)} \qquad (4)$$

where $\hat{\Gamma}^{(1)}$ is the reconstructed matrix from $W^{(1)}$ and $U^{(1)}$. Figure 2 gives some original face images and their corresponding reconstructed face images with $M_1 = 25$. The top images are the reconstructed face images($\hat{\Phi}_i = \hat{\Gamma}_i^{(1)} + \Psi$), the middle images are the corresponding original face images, and the bottom images are the residue images ($\Gamma_i^{(2)} = \Gamma_i^{(1)} - \hat{\Gamma}_i^{(1)}$). From the reconstructed matrices, we

can find that the details of the faces are lost. That means what $W^{(1)}$ describe can be looked as low-pass filtered images. The residue images are the corresponding high-pass filtered images. Observing the reconstructed matrices, some images cannot be reconstructed on a reasonable resolution which indicate that first –order features cannot describe these images well. The worse the reconstructed matrices is, the more information is reserved in residue image. Since these residue images still contains rich information for the individual image, face features should be extracted from these residue faces again.

Let $A^{(2)} = \left[\Gamma_1^{(2)}\Gamma_2^{(2)}...\Gamma_M^{(2)}\right]$, $\lambda_i^{(2)}$ be the eigenvalues of $A^{(2)^T}A^{(2)}$ and $v_i^{(2)}$ be the corresponding eigenvectors of $A^{(2)^T}A^{(2)}$. Then $A^{(2)^T}A^{(2)}v_i^{(2)} = \lambda_i^{(2)}v_i^{(2)}$. Based on the discussion above, the eigenvectors of $A^{(2)}A^{(2)^T}$ are $u_i^{(2)} = A^{(2)}v_i^{(2)}$. Therefore we can project a residue face image $\Gamma^{(2)}$ onto only $M_2 << M$ dimensions by computing $W^{(2)} = \left\{w_k^{(2)}\right\}$, where

$$w_k^{(2)} = u_k^{(2)^T}\Gamma^{(2)} \qquad (5)$$

and $1 \le k \le M_2$. Since $u_k^{(2)}$ are the eigenvectors of the residue face image, we call $u_k^{(2)}$ the second -order eigenfaces and $w_k^{(2)}$ the second –order features.

Let $U^{(2)} = \left[u_1^{(2)}u_2^{(2)}...u_{M_2}^{(2)}\right]$, Eq.(5) can be written as

$$\begin{aligned} W^{(2)} &= U^{(2)^T}\Gamma^{(2)} \\ &= U^{(2)^T}\left(\Gamma^{(1)} - \hat{\Gamma}^{(1)}\right) \\ &= U^{(2)^T}\left(\Gamma^{(1)} - U^{(1)+}W^{(1)}\right) \\ &= U^{(2)^T}\left(\Gamma^{(1)} - U^{(1)+}U^{(1)^T}\Gamma^{(1)}\right) \\ &= \left(U^{(2)^T} - U^{(2)^T}U^{(1)+}U^{(1)^T}\right)\Gamma^{(1)} \end{aligned} \qquad (6)$$

Let $U_2 = \left(U^{(2)^T} - U^{(2)^T}U^{(1)+}U^{(1)^T}\right)^T$, then

$$W^{(2)} = U_2^T\Gamma^{(1)} \qquad (7)$$

Since U_2 is a constant transform matrix and it is just calculated once, it will not effect the efficiency of computation. The face images can be described with $\Omega(\Phi) = \left[w_1^{(1)}, w_2^{(1)}, \ldots, w_{M'_1}^{(1)}, w_1^{(2)}, w_2^{(2)}, \ldots, w_{M_2}^{(2)}\right]^T$, where $1 \le M_1' \le M_1$. The computational burden does not increase in computing $\Omega(\Phi)$ compared with only computing features from eigenfaces U. For the convenience of discussion, the residue images are called second –order residue image and the original face images are called first –order residue images (though it seems it is better to call the original images as 0^{th}-order residue images).

The first-order eigenfeatures describe the characteristics of original images and the second-order eigenfeatures depict the characteristics of high-passed images. These characteristics can be used for different applications.

In lighting-invariant case, the view-angles of the images are almost the same, but the lighting conditions are different. The light can come from left, right, or both. Also the faces can be light or dark. In this situation, the features of images should be extracted after filtering. The original face image contains data of lighting feature, and the first–order eigenfeature also contains data of lighting feature. That means the first-order eigenfeatures are not suitable in this case. The second-order eigenfeature is obtained by subtracting the first-order eigenfeature from the original face image, thus removing the data of lighting feature. Thus, the second-order eigenfeatures have no influence by the lighting, and are suitable for use in face recognition that does not influenced by the lighting. On the other hand, when we consider view-angle-invariant case, the images of the same person are taken under the almost the same lighting condition but the view-angles or poses are not the same. In this situation, both the first-order and second-order eigenfeatures are important to describe the faces.

The first-order eigenfeature is obtained by processing the original face image through a low pass filter to extract, not the detail, but general feature of the face. Thus the first-order eigenfeature can provide approximately the same feature even if face images are obtained in different view-angles. Thus, in the cases where the view-angles may change, the first-order eigenfeature is used in addition to the second-order eigenfeature so as to obtain features which will not be influenced by the view-angle.

Therefore we will use second-order eigenfeatures as face descriptor to describe lighting-invariant situation and both of the first-order and second-order eigenfeatures as face descriptor to describe view-angle-invariant situation.

When we consider face description, an important characteristic is symmetry of faces. The faces of most of the people are symmetric. Thus we can consider to use the mirrored face image to represent the same person. Thus the eigenfeatures of the original image and the mirrored image can both represent the same person. Therefore, we can use the linear combination of the eigenfeatures of the two images to represent the original image. In order to discriminate between the original image and the mirrored image, different weights can be used to calculate features.

Suppose Φ be the original image and Φ' be the mirrored image of Φ. Then the adjusted eigenfeature should be

$$\overline{w}_i^{(1)}(\Phi) = w_i^{(1)}(\Phi) + c \cdot w_i^{(1)}(\Phi')$$

and

$$\overline{w}_i^{(2)}(\Phi) = w_i^{(2)}(\Phi) + c \cdot w_i^{(2)}(\Phi')$$

where $0 \le c \le 1$ is the weight for adjustment. In order to simplify the computation, the computational order can be rearranged.

Since $w_i^{(1)}(\Phi') = u_i^{(1)^T} \Gamma'^{(1)} = u_i^{(1)'^T} \Gamma^{(1)}$,

$$\begin{aligned}\overline{w}_i^{(1)}(\Phi) &= w_i^{(1)}(\Phi) + c \cdot w_i^{(1)}(\Phi') \\ &= u_i^{(1)^T} \Gamma^{(1)} + c \cdot u_i^{(1)'^T} \Gamma^{(1)} \\ &= \left(u_i^{(1)^T} + c \cdot u_i^{(1)'^T}\right) \Gamma^{(1)}\end{aligned}$$

where $u_i^{(1)'^T}$ is the mirrored eigenface of $u_i^{(1)^T}$. Figure 1 shows the procedure to get $u_i^{(1)'^T}$ from $u_i^{(1)^T}$. With the same method, we can obtain

$$\begin{aligned}\overline{W}^{(1)} &= U^{(1)^T} \Gamma^{(1)} + c \cdot U^{(1)^T} \operatorname{flip}\left(\Gamma^{(1)}\right) \\ &= U^{(1)^T} \Gamma^{(1)} + c \cdot \operatorname{flip}\left(U^{(1)^T}\right) \Gamma^{(1)} \\ &= \left(U^{(1)^T} + c \cdot \operatorname{flip}\left(U^{(1)^T}\right)\right) \Gamma^{(1)} \\ &= \overline{U}_1 \Gamma^{(1)} \qquad (8)\end{aligned}$$

and

$$
\begin{aligned}
\overline{W}^{(2)} &= U_2^T\Gamma^{(1)} + c\cdot U_2^T\,\mathrm{flip}\left(\Gamma^{(1)}\right)\\
&= U_2^T\Gamma^{(1)} + c\cdot \mathrm{flip}\left(U_2^T\right)\Gamma^{(1)}\\
&= \left(U_2^T + c\cdot \mathrm{flip}\left(U_2^T\right)\right)\Gamma^{(1)}\\
&= \overline{U}_2\Gamma^{(1)}
\end{aligned}
\tag{9}
$$

where mirror() is the mirror function to mirror matrix in left/right direction. With Eq.(8) and Eq.(9), the first-order eigenfaces and second-order eigenfaces and can be adjusted to $\overline{U}_1$ and $\overline{U}_2$.

The eigenfeatures discussed above can be used to describe huma faces effectively. However, if the eigenfeatures are looked as features for face recognition or related application, the eigenfeatures should be normalized since the range of the eigenfeatures are not the same.

One of the reasonable normalization method is to divide the eigenfeatures by the corresponding standard deviation of eigenfeatures in the training set. Let $\sigma_i^{(j)}$ be the standard deviation of $w_i^{(j)}$ in the training set, where j=1,2 denotes the first- or second-order eigenfeatures. Then normalized eigenfeatures of image Φ are

$$\widetilde{w}_i^{(j)}(\Phi) = \frac{\overline{w}_i^{(j)}(\Phi)}{\sigma_i^{(j)}}$$

The similarity of face images is simply defined as the weighted distance between normalized projections:

$$\delta(\Phi_1,\Phi_2) = \sum_{i=1}^{M'_1}\left\|a_i^{(1)}\left(\widetilde{w}_i^{(1)}(\Phi_1) - \widetilde{w}_i^{(1)}(\Phi_2)\right)\right\| + \sum_{j=1}^{M_2}\left\|a_j^{(2)}\left(\widetilde{w}_j^{(2)}(\Phi_1) - \widetilde{w}_j^{(2)}(\Phi_2)\right)\right\| \tag{10}$$

If $a_i^{(1)} = 0$, the similarity of face images will be measured only with second –order eigenfeatures for lighting-invariant face description. For view-angle-invariant case, both first- and second-order eigenfeatures are necessary. The weights are chosen as follows:

$$a_i^{(1)} = \mathrm{round}\left(\frac{\sqrt{\sigma_i^{(1)}}}{100}\right) \text{ and } a_j^{(2)} = \mathrm{round}\left(\frac{\sqrt{\sigma_j^{(2)}}}{100}\right)$$

The weights can also select other numbers according the applications. In fact, the weights can be embedded into adjusted eigenfaces to reduce the

computation, and the normalization parameters can also been moved to eigenface matrix. In order to save the storage, the eigenface matrix and eigenfeatures should be quantized into integers from floating points.

Let $\hat{u}_i^{(j)} = \text{Round}\left(a_i^{(j)} \dfrac{u_i^{(j)}}{\sigma_i^{(j)}} R^{(j)}\right)$, where $R^{(j)} = \dfrac{128}{\max\limits_i \left(abs\left(a_i^{(j)} \dfrac{u_i^{(j)}}{\sigma_i^{(j)}} \right)\right)}$, and Round() is the round function, and j=1,2. The eigenfeatures can be quantized with

$$\hat{w}_i^{(j)}(\Phi) = \begin{cases} -128, & if \quad \text{Round}\left(d^{(j)}\hat{u}_i^{(j)}\Gamma^{(1)}\right) < -128 \\ 127, & if \quad \text{Round}\left(d^{(j)}\hat{u}_i^{(j)}\Gamma^{(1)}\right) > 127 \\ \text{Round}\left(d^{(j)}\hat{u}_i^{(j)}\Gamma^{(1)}\right), & \text{otherwise} \end{cases}, \qquad (10\text{-}1)$$

where $d^{(j)} = \dfrac{128}{\max\limits_{i,k}\left(abs\left(\dfrac{\hat{u}_i^{(j)}}{R^{(j)}} \Gamma_k \right)\right) R^{(j)}}$, Γ_k is the images in the training set. The feature set can be written as $\hat{W}^{(1)} = \{\hat{w}_i^{(1)}\}$ and $\hat{W}^{(2)} = \{\hat{w}_j^{(2)}\}$. Therefore, each eigenfeature can be quantized to 8 bits.

Further, in order to reduce the size of total eigenfeatures, the eigenfeatures can be re-quantized according to their standard deviation of the training set. This can be considered as the trade-off between the size of face descriptor and the retrieval accuracy. According to our experiments, the bits for each eigenfeature can be allocated as follows:

$$N_i^{(j)} = \text{round}\left(\log_2 \left(\frac{\sigma_i^{(j)}}{\min\left(\sigma^{(j)}\right)} \times 16 \right) \right)$$

where $\min\left(\sigma^{(j)}\right)$ is the minimum of the standard deviations of the j-th order eigenfeatures. Though different eigenfeature allocate different bits, the range is still remains [-128,127]. With this quantization strategy, the size of face descriptor can reduce about 40% while the retrieval accuracy drop about 1% to 2%. If the original quantization strategy is acceptable, then the further quantization is not necessary. Here a normalizing and clipping procedure example is given to further quantize and compact the feature from the equation (10-1) and each eigenfeature can be represented as unified 5 bits:

$$\widehat{w}_i = \begin{cases} 0, & if \quad \widehat{w}_i / Z < -16 \\ 31, & if \quad \widehat{w}_i / Z > 15 \\ round(w_i / Z + 16), & \text{otherwise} \end{cases}$$

where Z=16384*8 is the normalization constant from our experience.

With the above formulae, the distance between two face images Φ_1, Φ_2 for view-angle-invariant description, can be calculated as

$$\delta(\Phi_1, \Phi_2) = \sum_{i=1}^{M'_1} \left\| \widehat{w}_i^{(1)}(\Phi_1) - \widehat{w}_i^{(1)}(\Phi_2) \right\| + \sum_{j=1}^{M_2} \left\| \widehat{w}_j^{(2)}(\Phi_1) - \widehat{w}_j^{(2)}(\Phi_2) \right\| \qquad (11)$$

and the distance distance between two face images Φ_1, Φ_2 for lighting-invariant description, can be calculated as

$$\delta(\Phi_1, \Phi_2) = \sum_{j=1}^{M_2} \left\| \widehat{w}_j^{(2)}(\Phi_1) - \widehat{w}_j^{(2)}(\Phi_2) \right\| \qquad (12)$$

In order to further compact the face descriptor, variable length coding can be used to the quantized eigenfeatures. The Huffman coding and arithmetic coding can be used to do the work.

The code tables can be computed as follows:

1) for the images in the training set, calculating the eigenfeatures;
2) quantizing the eigenfeatures with the stretegy discussed above;
3) for the quantized eigenfeatures with the same bit allocation, computing the probability of each quantization level;
4) calculating the variable length codes for all quantization levels;
5) calculating all code tables with the steps 3) and 4) for all bit allocation cases.

With this method, the face descriptor can be further compacted. Correspondingly, The coded face descriptor should be decoded before the distance between two face descriptors can be calculated.

According to our observation, the first-order eigenfeatures itself can also be used to describe view-angle- and lighting-invariant face features. The view-angle-invariant face features can be the eigenfeatures extracted from the eigenfaces corresponding to the top N largest eigenvalues. The lighting-invariant face features can be the eigenfeatures extracted from the eigenfaces corresponding to the top k-th to N-th largest eigenvalues where 0<k<N. In general, 4≤k≤10 and 40≤N≤60. We recommend the use of k = 8, N = 40 and total eigenface number is 48. Figure 4 and Figure 5 show, respectively, a flow chart for extracting eigenfeatures that will not be influenced by the lighting, and a flow chart for extracting eigenfeature that will not be influenced by the view-angle.

In Figure 4 showing the method of extracting eigenfeatures that will not be influenced by the lighting, the following steps are provided.

Step 410: Calculate the adjusted second -order eigenface matrix.

Step 420: Get the adjusted second -order engenfeatures.

Step 430: Select features to describe faces from the adjusted second -order eigenfeatures.

Step 440: Code the quantized eigenfeatures with VLC. This step can be omitted.

In Figure 5 showing the method of extracting eigenfeature that will not be influenced by the view-angle, the following steps are provided.

Step 510: Calculate the adjusted first -order eigenface matrix.

Step 520: Calculate the adjusted second -order eigenface matrix.

Step 530: Get the adjusted first -order eigenfeatures.

Step 540: Get the adjusted second -order eigenfeatures.

Step 550: Quantize the adjusted first-order eigenfeatures and the adjusted second -order eigenfeatures.

Step 560: Select features to describe faces from the adjusted first -order and second -order eigenfeatures.

Step 570: Code the quantized eigenfeatures with VLC. This step can be omitted.

This invention is very effective for describing human faces. Since the second-order eigenfaces can be calculated only once with the training face images, the second-order features can be obtained as efficient as first-order features. Since detailed information can be revealed with high-order eigenfeatures, the performance of the combination of first-order and second-order eigenfeatures is better in view-angle-invariant face description compared with the same number of first -order eigenfeatures. The second-order eigenfeatures has much better lighting-invariant face description capability compared with the first-order eigenfeatures. This invention is very effective and efficient in describing human faces. The description method can be used in internet multimedia database retrieval, video editing, digital library, surveillance and tracking, and other applications using face recognition and verification broadly.

The present disclosure relates to subject matter contained in priority Japanese Patent Application No. 2000-385126, filed on December 19, 2000, the contents of which is herein expressly incorporated by reference in its entirety.